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Coordination Models and Techniques for Big Data and Machine Learning Systems

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Learning objectives

- **Analyze the role of coordination techniques, their complexity and diversity in big data/ML systems**
- **Understand and apply orchestration models, common tools and design patterns**
- **Understand and apply choreography models, common tools and design patterns**
- **Understand, define and develop ML Model Serving**

Coordination complexity and diversity

Examples of common tasks

Discussion:
- **ML phases & tasks**
- **Software stack**
- **Execution environments**
  - Computing resources
- **R3E**

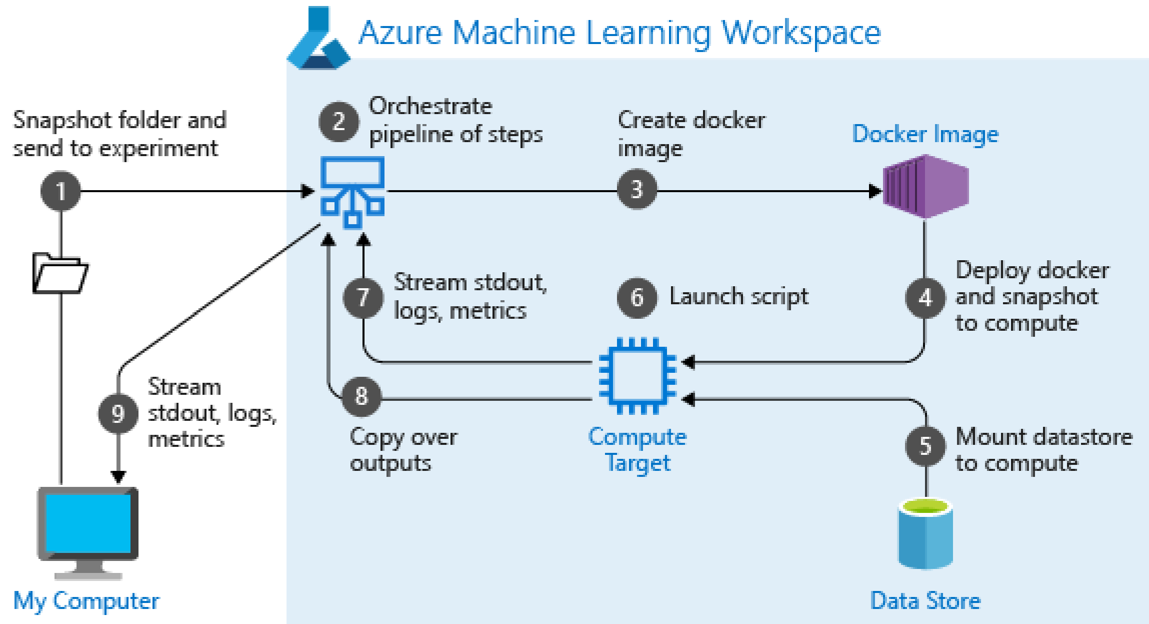
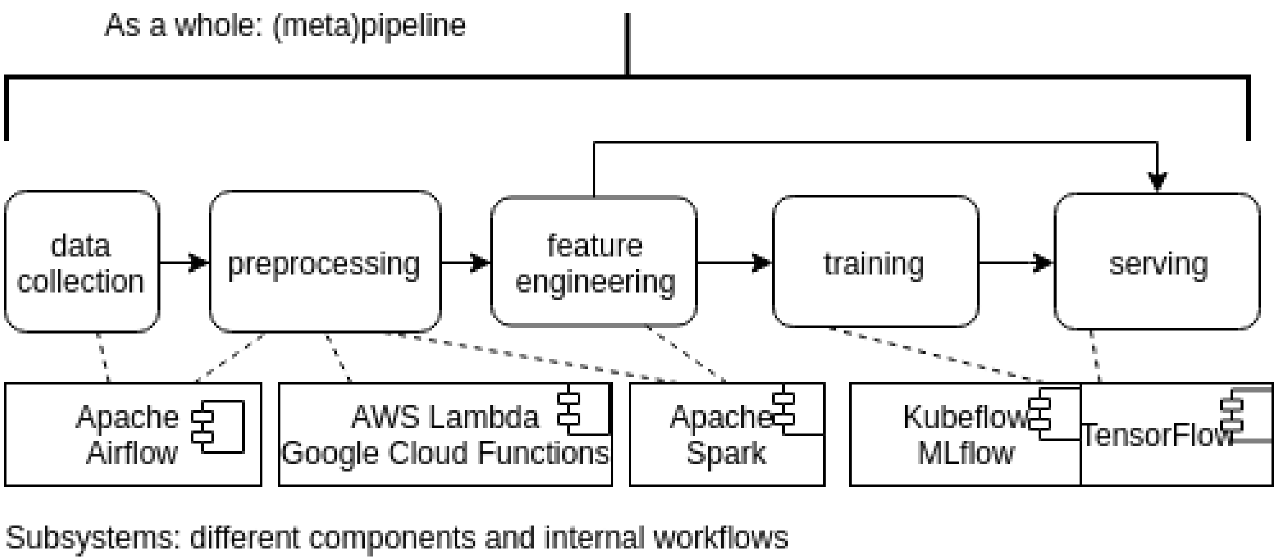


Figure source: https://docs.microsoft.com/en-us/azure/machine-learning/concept-ml-pipelines

Recall: big data/ML systems

- **Multiple levels:**
  - Meta-workflow or -pipeline
  - Inside each phase: pipeline/workflow or other types of programs

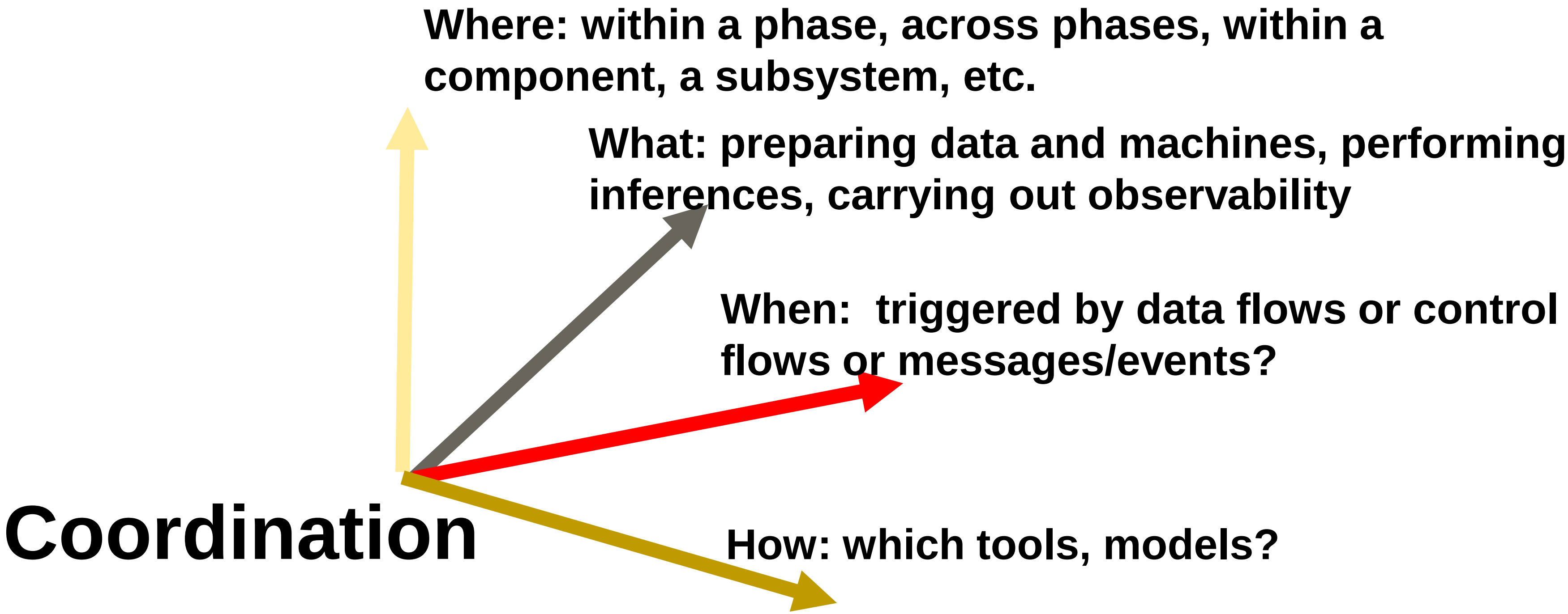


Automation vs manual tasks: share your current way?

Main issues related to coordination

- **How to coordinate phases and tasks in big data/ML systems**
  - automation is an important requirement, why?
- **How to prepare artefacts and resources for big data/ML systems**
- **How to manage tests and experiments**
  - trial computing configurations, inputs/results collection
- **How to control for assuring R3E for the pipeline execution**
  - end-to-end R3E requires coordination
  - issues in internal and external services

W3H: what, when, where and how for coordination



Diversity and Complexity

- **Diversity**
  - so many tools/frameworks in a single big data/ML system
    → *a single coordination model/tool might not be enough*
  - there exist many coordination systems (included your specific implementation)
    → *which ones should we select?*
- **Complexity, due to**
  - integration models with big data/ML components and infrastructures
  - very large-scale
  - runtime management: performance, failures, states

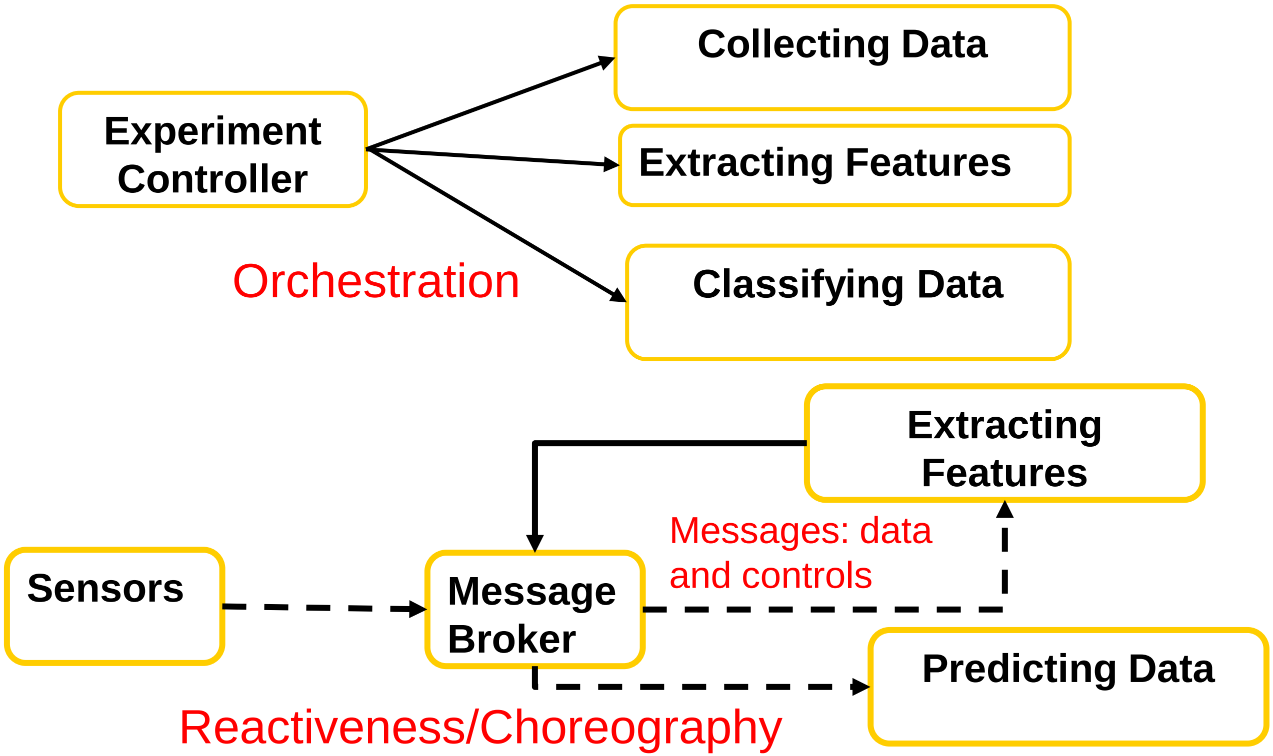
Key notions

- **Workflow and Task/Activity/Step abstraction**
  - a task can encapsulate a “complex workflow”
- **Big Data/ML software frameworks**
  - for implementing big data/ML capabilities
- **Platform services for coordination**
  - services offering features/functionality for executing “tasks”
  - single or multiple providers?
- **Execution environments and resources**
  - single platform or cross (heterogeneous) platforms

Coordination styles

- **Coordination models for Big Data/ML systems**
  - orchestration and reactiveness/choreography
- **Orchestration**
  - task graphs and dependencies are based on control or data flows
  - dedicated orchestrator: tasks triggered based on completeness of tasks or the availability of data
- **Reactiveness/choreography**
  - follow reactive model: tasks are reacted/triggered based on messages

Orchestration and Reactiveness



System issues impacting coordination

- **Main situations:**
  - within the same system/infrastructure
    - *all services and computing resources belong to the same platform/infrastructure*
    - *e.g., running everything with Google Cloud or Microsoft Azure*
  - across systems/infrastructures
    - *services in different clouds or cloud data centers*
    - *e.g., Edge-cloud infrastructures*
  - with the same software stack or not?
- **How such situations would affect the coordination?**

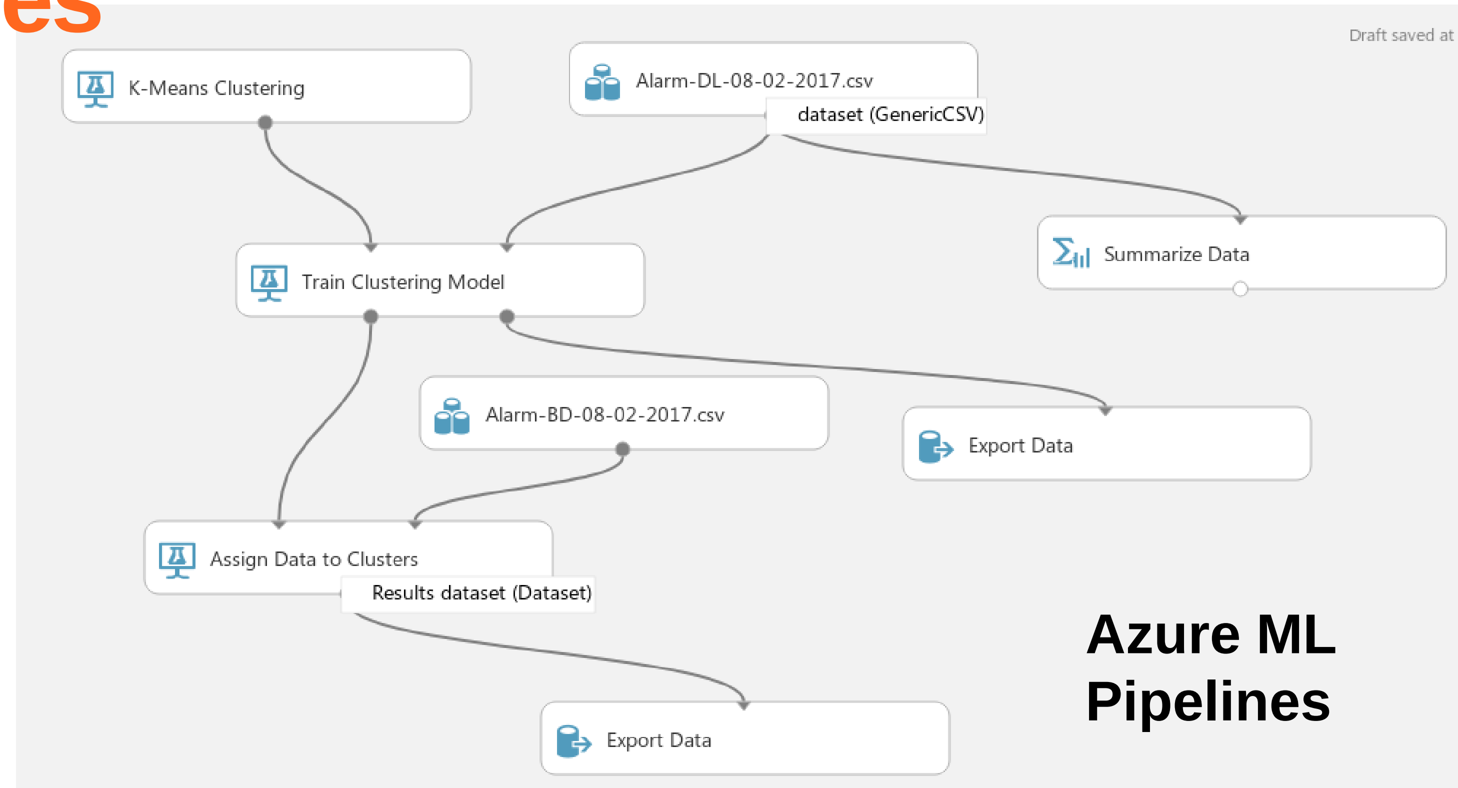
Coordination with workflow techniques

The orchestration style

Orchestration architectural style: design

- **Workflow architectures are known**
  - Big Data/ML systems: leverage many types of services and cloud technologies
- **Required components**
  - workflow/pipeline specifications/languages (also UI)
  - data and computing resource management
  - orchestration engines (with different types of schedulers)
- **Execution environments**
  - cloud platforms (e.g., VMs, containers, Kubernetes)
  - heterogenous computing resources (PC, servers, Raspberry PI, etc.)

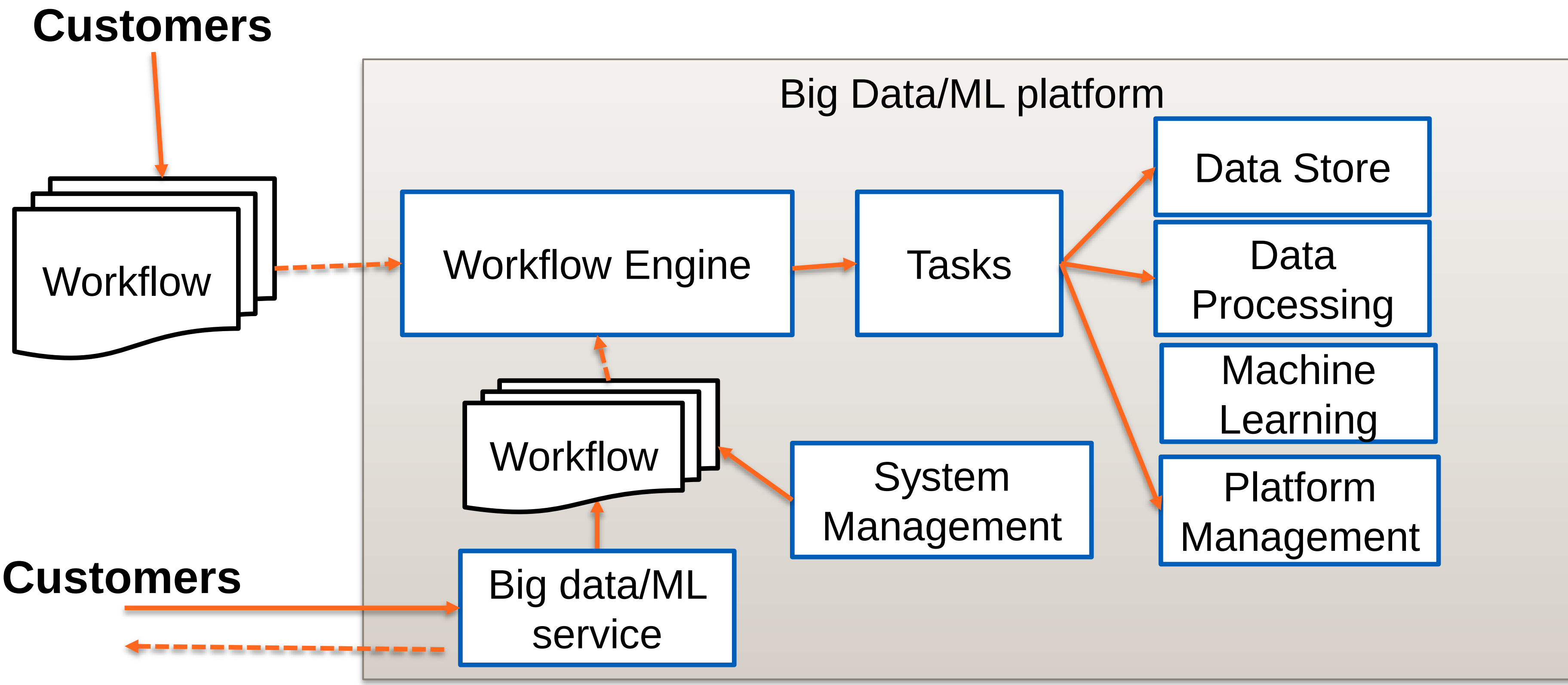
Example: workflow used in ML pipelines



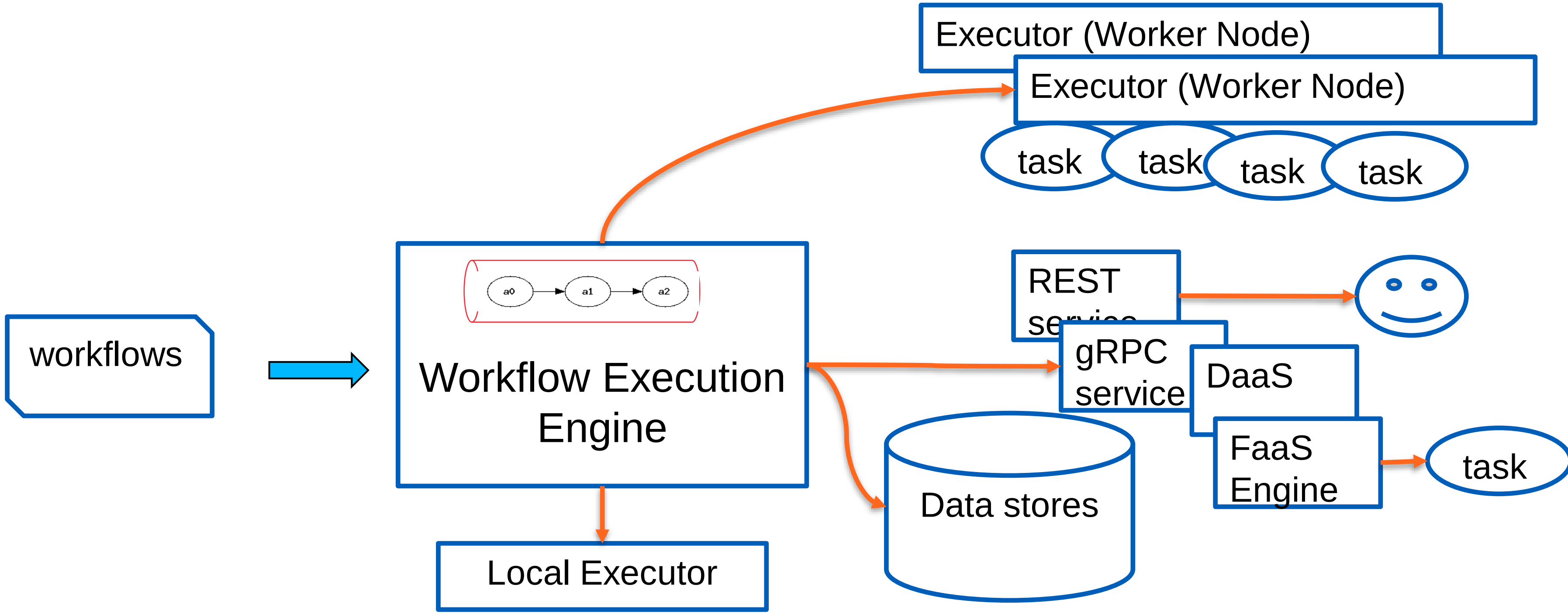
So what is behind the scene?

Azure ML Pipelines

Workflows in big data/ML systems



Common workflow execution models



Executors: containers, VMs, common OS processes

Key components

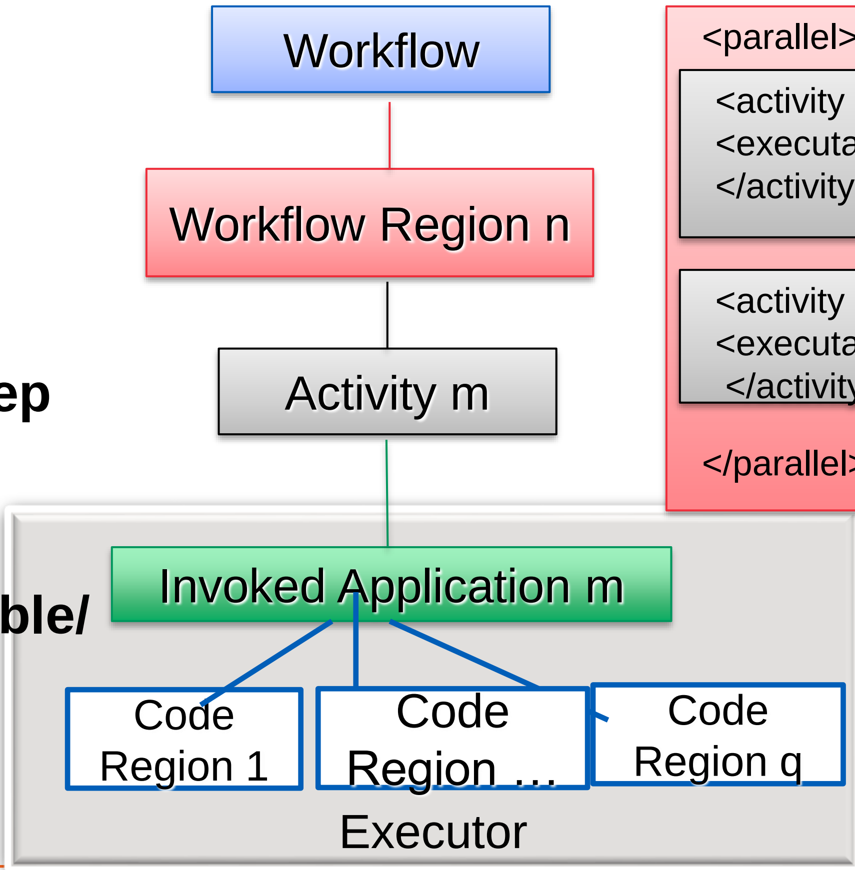
- **Tasks/Activities**
  - describe a single work (it does not mean small)
  - tasks can be carried out by humans, executables, scripts, batch applications, stream applications and services.
- **Workflow Languages**
  - how to structure/describe tasks, dataflows, and control flows
- **Workflow Engine**
  - execute the workflow by orchestrating tasks
  - usually call remote services to run tasks

Structured view of workflows

abstract example

Task/Step

Service /executable/ script




```
<parallel>
  <activity name="mTask1">
  <executable name="mTask1"/>
  </activity>

  <activity name="pTask2">
  <executable name="cbpprediction"/>
  </activity>
</parallel>
```

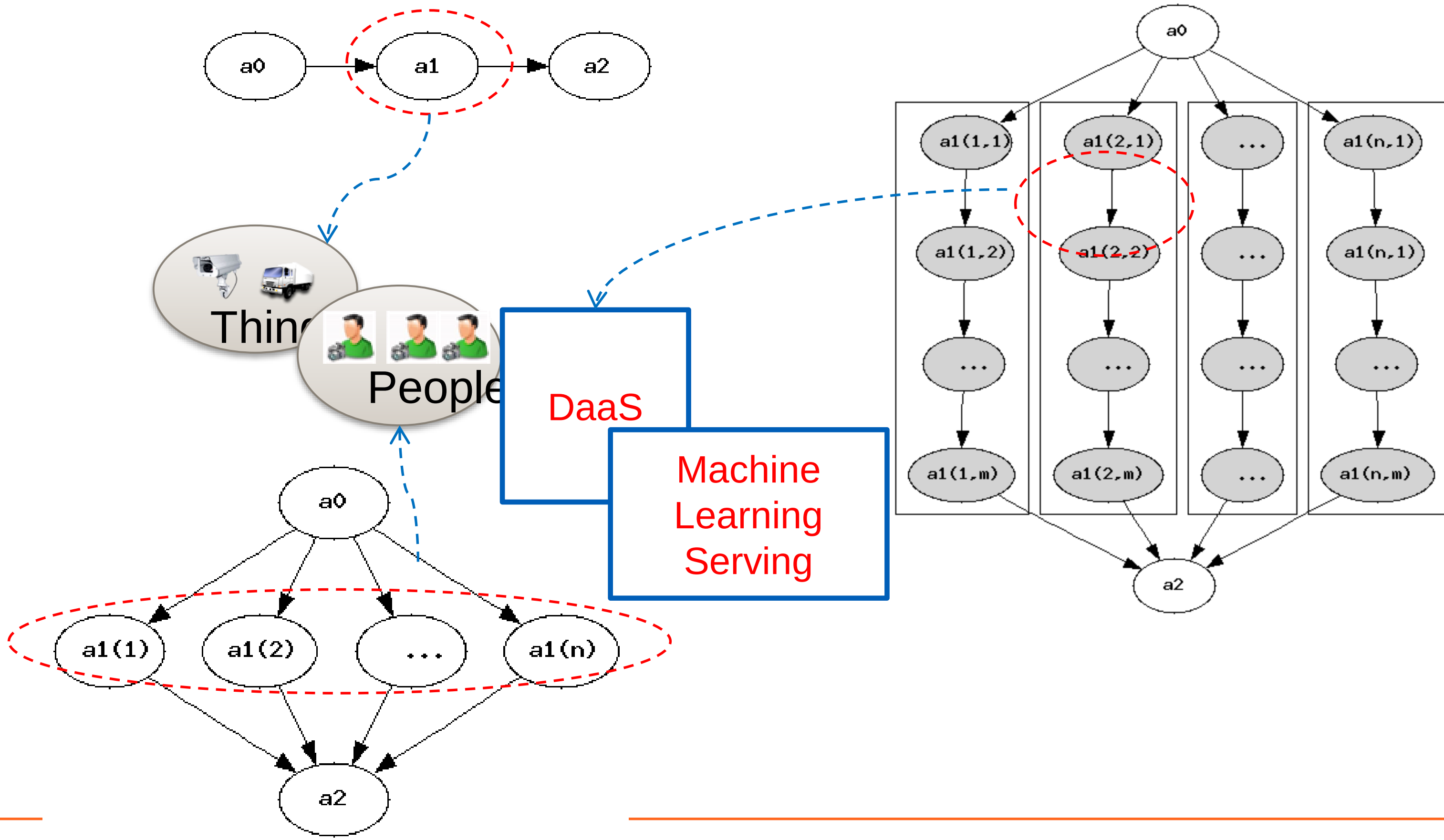
```
cbpprediction.py
def find_target_regression_model(dataset):
    selecteddata=selecteddata[TARGET_FEATURES].dropna()

    target_lin_reg =LinearRegression()
    target_lin_reg.fit(X,Y)
```

Structured view

- **Invoked applications within a task/activity**
  - can be a containerized service, script, python program, a function, etc.
  - can be designed for different purposes: e.g. computation, management or prediction
- **Encapsulating the whole workflow**
  - the whole workflow can be encapsulated with in a service
  - thus the whole workflow can be invoked via a service call for multiple consumers

Tasks orchestration



Runtime aspects

- **Parallel and distributed execution**
  - tasks are deployed and running in different machines
  - multiple workflows are running
- **Long running**
  - can be hours!
- **Checkpoint and recovery**
- **Monitoring and tracking**
  - which tasks are running, where are they?
- **Stateful management**
  - dependencies among tasks w.r.t control and data

Describing workflows

- **Programming languages with procedural code**
  - general- and specific-purpose programming languages, such as Java, Python, Swift
  - common ways in big data and ML platforms
- **Descriptive languages with declarative schemas**
  - BPEL, YAML, and several languages designed for specific workflow engines
  - common in business and scientific workflows
  - YAML is also popular for big data/ML workflows in native cloud environments

Workflow frameworks

- **Often running in the same infrastructure**
- **Task-driven or data-driven specification**
- **Generic workflows**
  - Use to implement different tasks, such as machine provisioning, service calls, data retrieval
    - *Examples: Airflow, Argo Workflows*
- **Specific workflows for specific purposes**
  - E.g., Kubeflow (https://github.com/kubeflow/pipelines)

Workflow frameworks

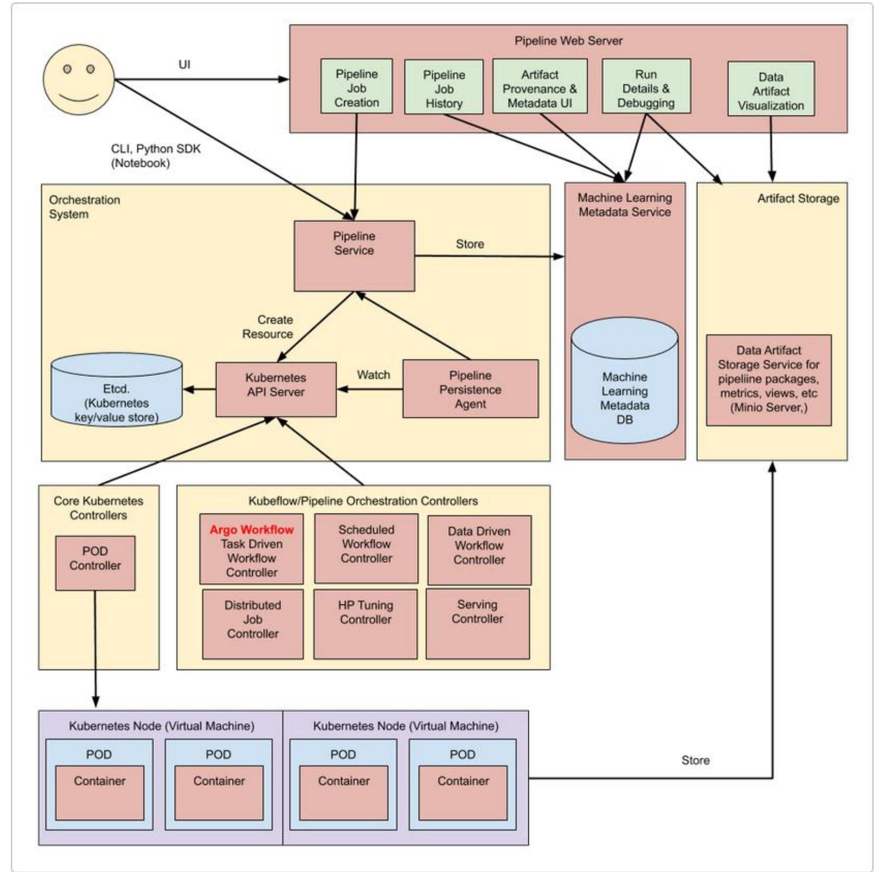
- **Apache Airflow**
  - https://airflow.apache.org/, also used by Google Composer
- **Argo**
  - https://argoproj.github.io/argo/, used in Kubeflow
- **Prefect**
  - https://www.prefect.io/
- **Uber Cadence**
  - https://github.com/uber/cadence

What purposes are for using workflows?

- **For coordinating big data/ML phases/stages in the pipeline**
- **For implementing tasks within a phase/stage**
  - implement data preprocessing task
  - implement training tasks
  - implement experiment management
  - batch model for machine learning serving
- **Which ones? No easy answer**
  - separate – as a framework/service
  - integrated within big data/ML frameworks

Examples: Kubeflow

- **End-to-end Orchestration**
- **Orchestration is based on workflows**
- **Using “Orchestration controllers”**

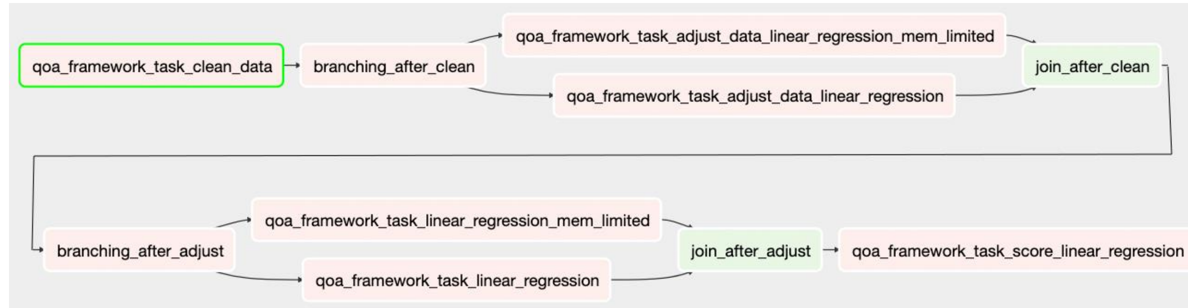


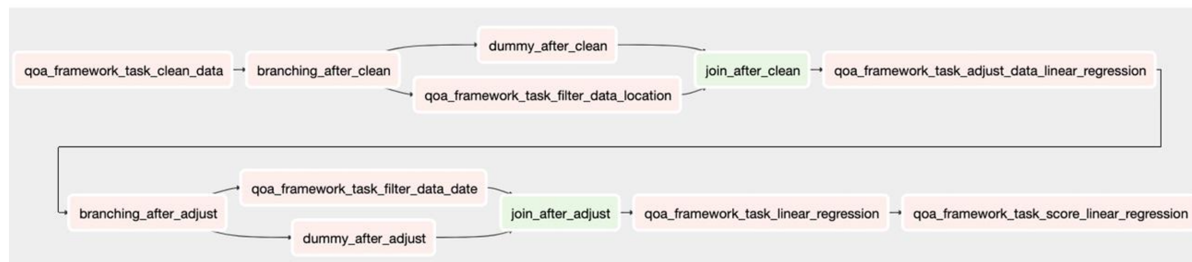
https://www.kubeflow.org/docs/pipelines/overview/pipelines-overview/

- Discussion: dealing R3E with ML workflows?
  - Where, What, When and How

Examples: Coordinating tasks

- Discussion: dealing R3E with ML workflows?
  - Where, What, When and How

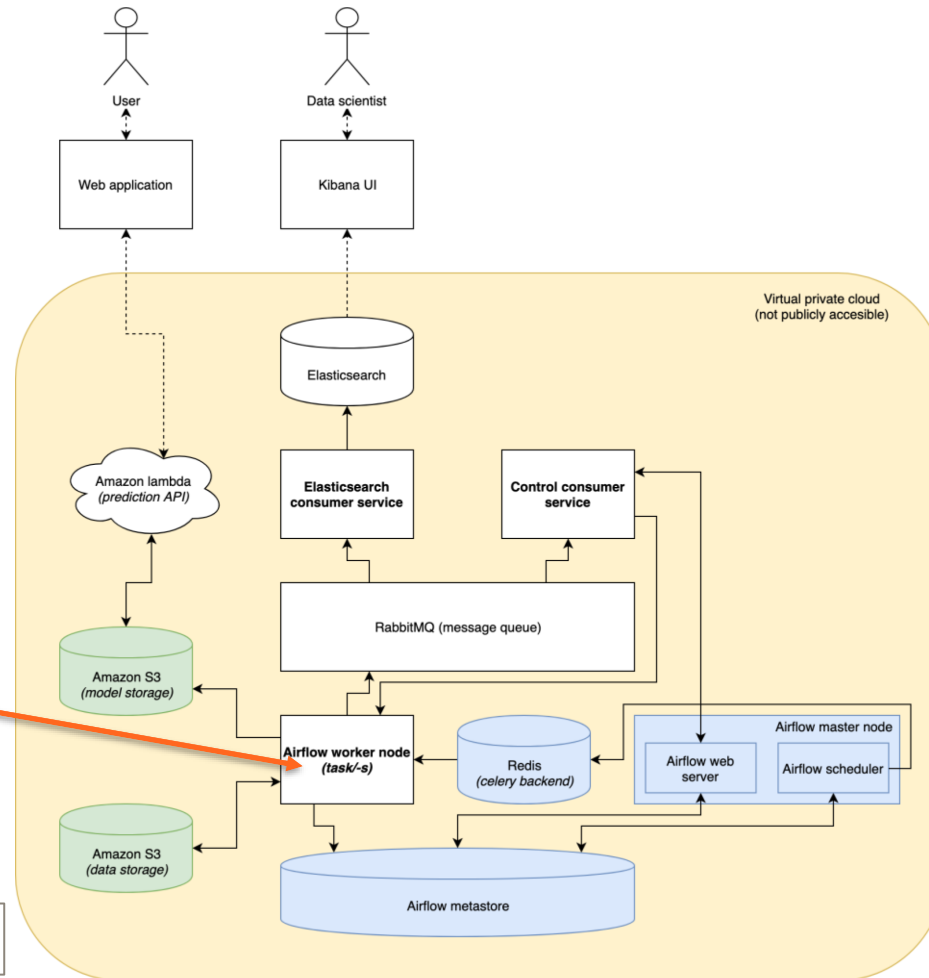




Source: Kreics Krists, „Quality of analytics management of data pipelines for retail forecasting,", Aalto CS Master thesis, 2019

Examples: Exchanging metrics for R3E coordination

Monitoring various metrics, including user-defined quality of data



Source: Kreics Krists, „Quality of analytics management of data pipelines for retail forecasting“, Aalto CS Master thesis, 2019

Example: Apache Beam

- **Goal: separate from data processing pipelines from backend execution engines**
  - Focus on pipeline design

Pipeline

Read data → Processing → …. → Store result

Flink

Apache Spark

Dataflow

Example: Apache Beam

- **https://beam.apache.org/**
- **Suitable for data analysis processes that can be divided into different independent tasks**
  - ETL (Extract, Transform and Load) & Data Integration
  - ML pipeline implementation
- **Execution principles:**
  - Mapping tasks in the pipeline to concrete tasks that are supported by the selected back-end engine
  - Coordinating task execution like workflows.

Example: Apache Beam Basic programming constructs

- **Pipeline:**
  - For creating a pipeline
- **PCollection**
  - Represent a distributed dataset
- **Transform**
  - [Output PCollection] = [Input PCollection] | [Transform]
  - Possible transforms: ParDo, GroupByKey, Combine, etc.
  - Partition: split the data

Example: Apache Beam

- **Data preprocessing and featuring engineering**
  - could also be for data validation
- **Preparation for training**
  - processing and partitioning data
- **Inferences**
  - implement inference functions which can be called within a pipeline, e.g. using ParDo()

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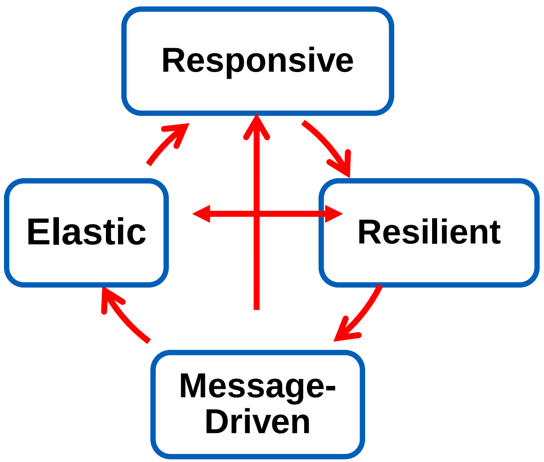
Coordination with messaging

The reactiveness/choreography

Choreography: Reactive systems for Big Data/ML

Do you remember key principles of reactive systems?

Reactive systems



Source: https://www.reactivemanifesto.org/

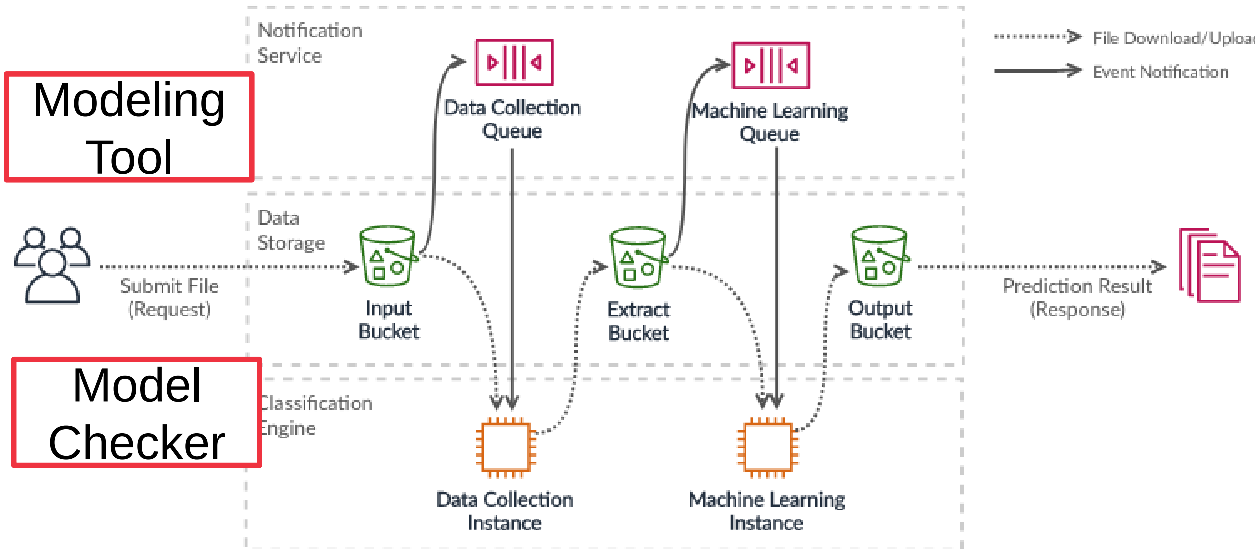
- Responsive: quality of services
- Resilient: deal within failures
- Elastic: deal with different workload and quality of analytics
- Message-driven: allow loosely coupling, isolation, asynchronous

Reactive systems for Big Data/ML: methods

- **Have different components as services**
  - components can come from different software stacks
  - components for doing computation as well as for data exchange
- **Elastic computing platforms**
  - platforms should be deployed on-demand in an easy way
- **Using messages to trigger tasks carried out by services**
  - messages for states and controls as well as for data
  - heavily relying on message brokers and lightweight triggers/controls (e.g., with serverless/function-as-a-service)

Examples: do-it-your-self ML classification for BIM

- Discussion: dealing R3E with ML workflows?
  - Where, What, When and How

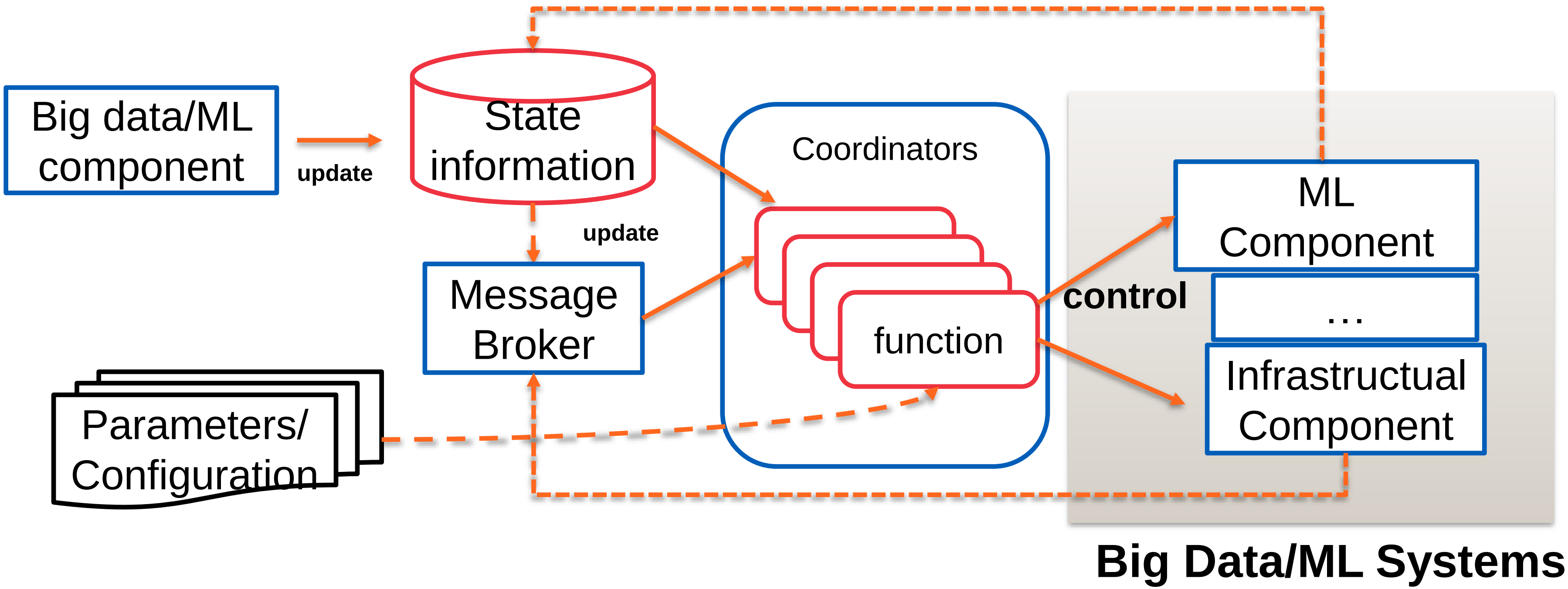


Source: Minjung Ryu, „Machine Learning-based Classification System for Building Information Models “, Aalto CS Master thesis, 2020

Which frameworks

- **Message brokers**
  - Kafka, RabbitMQ, Amazon SQS, …
  - types of messages and semantics must be defined clearly
- **Triggers and controls**
  - serverless/function-as-a-service can be used: trigger a function based on a message
    - *AWS Lambda, Google Cloud Function, Knative, Kubeless, OpenFaaS, Azure Functions*
    - *We are discussing to use serverless for "coordination"*
  - self-implementation of triggers listening messages

Common architecture



Example: Serverless for coordination

- **Training preparation**
  - before running a training: you move data from sources to stage, ship the code and prepare the environment
- **Coordination of ML phases**
  - do the coordination of three phases: data preprocessing, training and take the best model to deploy to a serving platform
- **Experiment results gathering**
  - you run experiments in different places. There are several logs of results, you gather them and put the result into a database

Serverless as functions within ML workflows

- **Tasks in ML can be implemented as a function**
- **Thus a workflow of functions can be used to implement ML pipelines**
  - Example: using serverless to implement data preprocessing

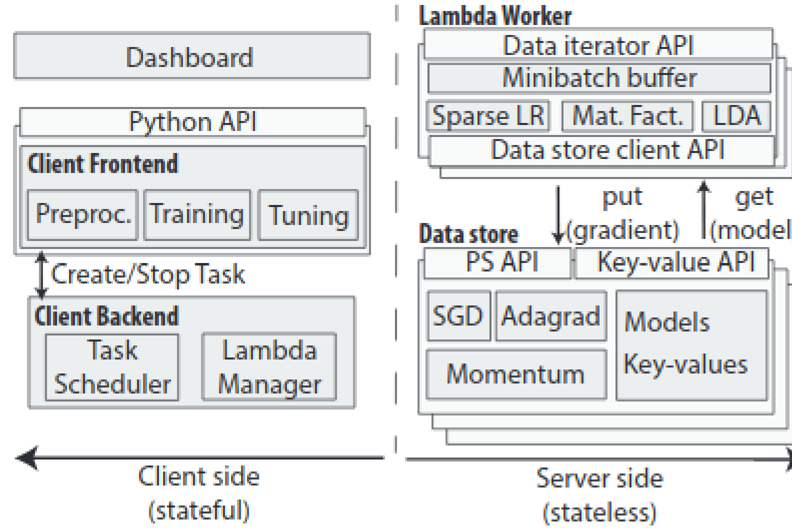


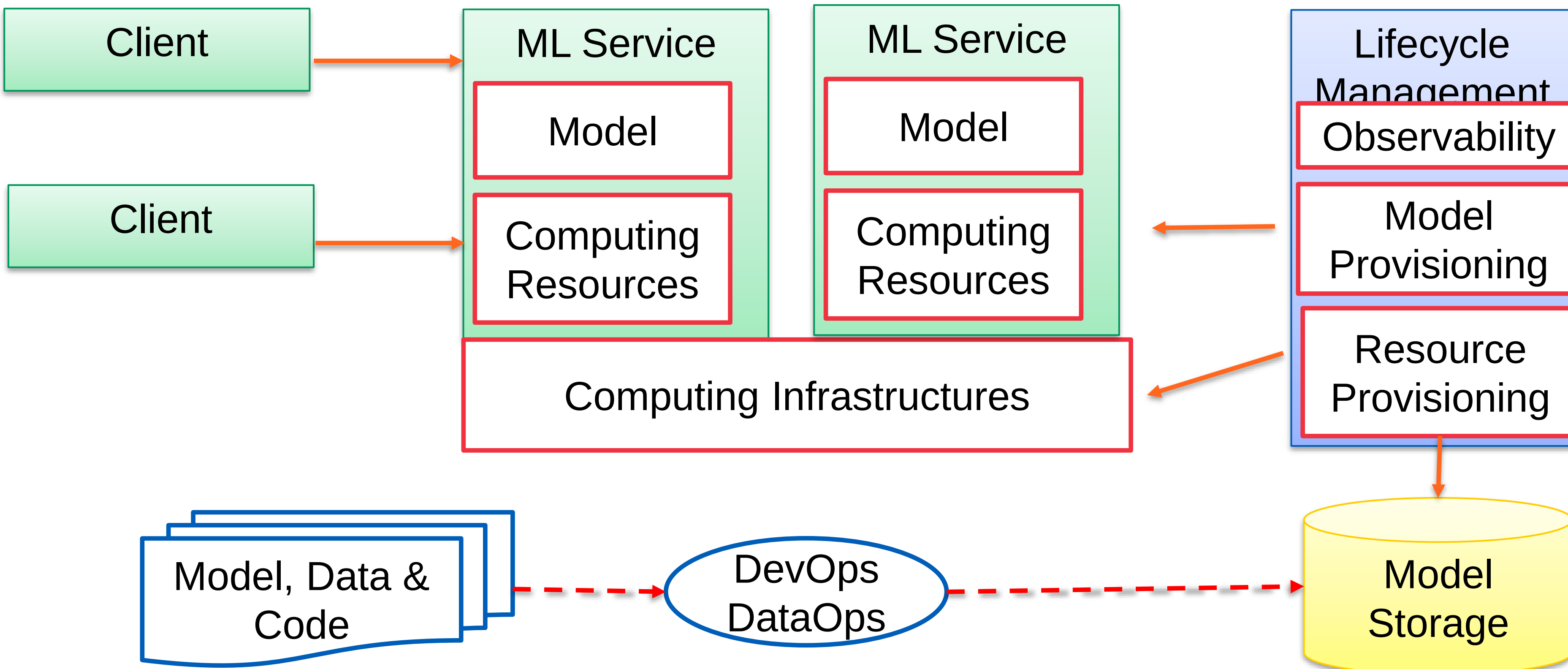
Figure source: Joao Carreira, Pedro Fonseca, Alexey Tumanov, Andrew Zhang, and Randy Katz. 2019. Cirrus: a Serverless Framework for End-to-end ML Workflows. In Proceedings of the ACM Symposium on Cloud Computing (SoCC '19). DOI:https://doi.org/10.1145/3357223.3362711

Dynamic ML Serving

ML Model Serving

- **Allow different versions of ML models to be provisioned**
  - runtime deployment/provisioning of models
  - "model as code" or "model as a service" → can be deployed into a hosting environment
- **Why? Anything related to R3E?**
  - concurrent deployments with different SLAs
  - A/B testing and continuous delivery for ML (https://martinfowler.com/articles/cd4ml.html)
- **Existing platforms**
  - increasingly support by different vendors as a concept of "AI as a service" (check https://github.com/EthicalML/awesome-production-machine-learning#model-deployment-and-orchestration-frameworks)

ML Model Serving design



ML Service

- **Long runtime inferencing services**
  - with well defined interfaces, know how to invoke models
  - accept continuous requests and serve in near-real time
- **Containerized service with REST/gRPC**
  - for on-demand serving or for scaling long running serving
- **Serverless function wrapping models**
  - short serving time
- **Batch serving**
  - not near real time serving due to the long inferencing time

Question: which forms are the best for which situations

Example: TensorFlow Extended Serving

- **Lifecycle**
  - Load, serving and unloading
- **Metrics & Policies**

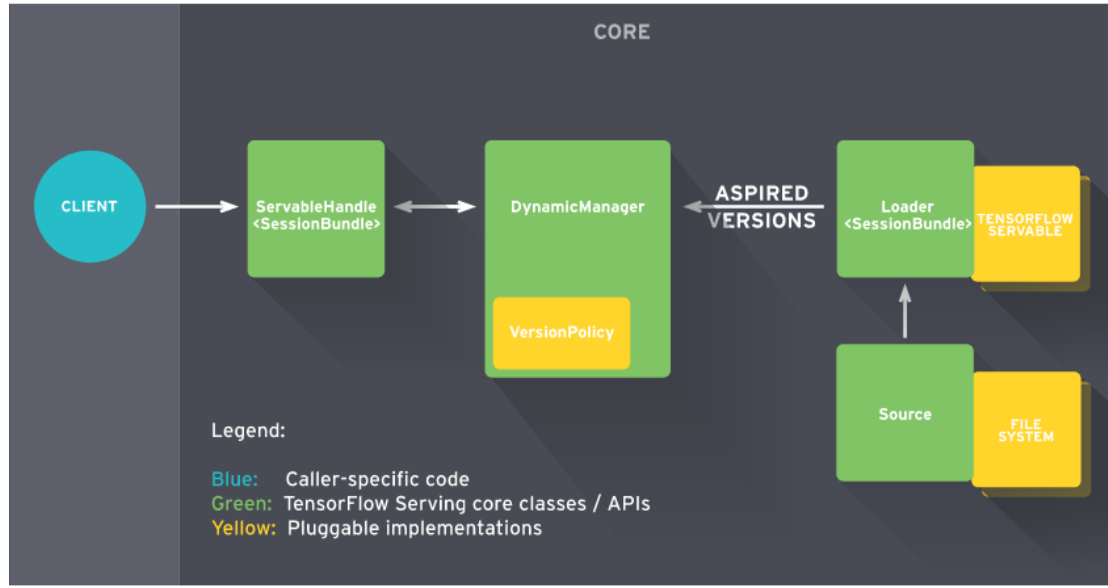
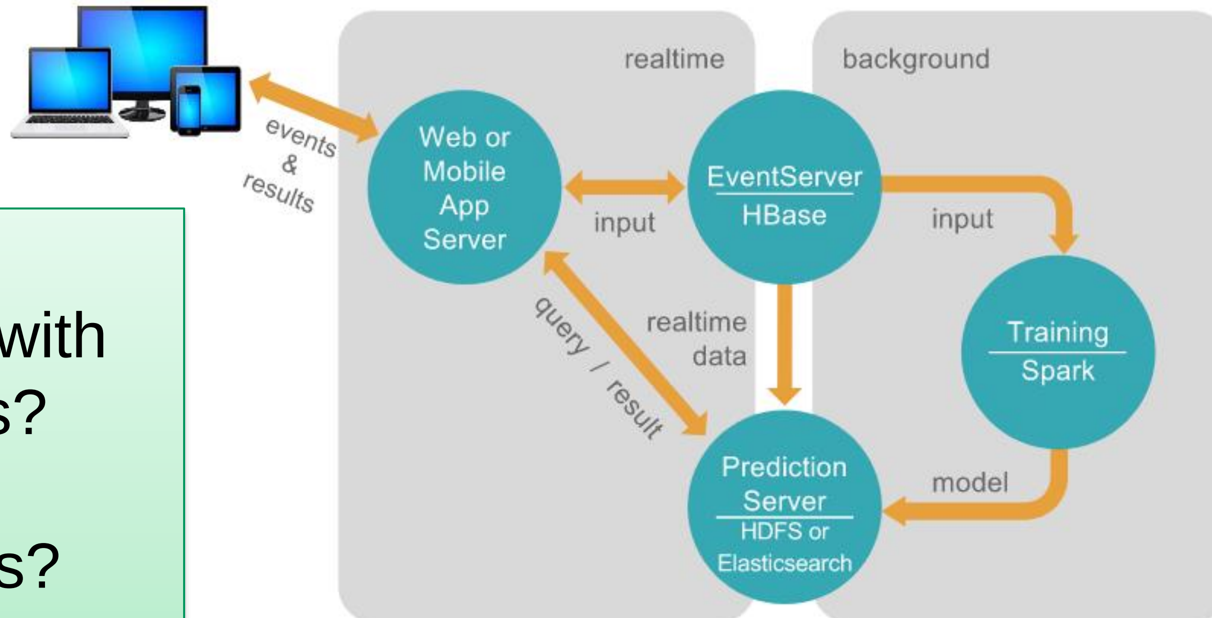


Figure source: https://www.tensorflow.org/tfx/serving/architecture

Example of Prediction.io

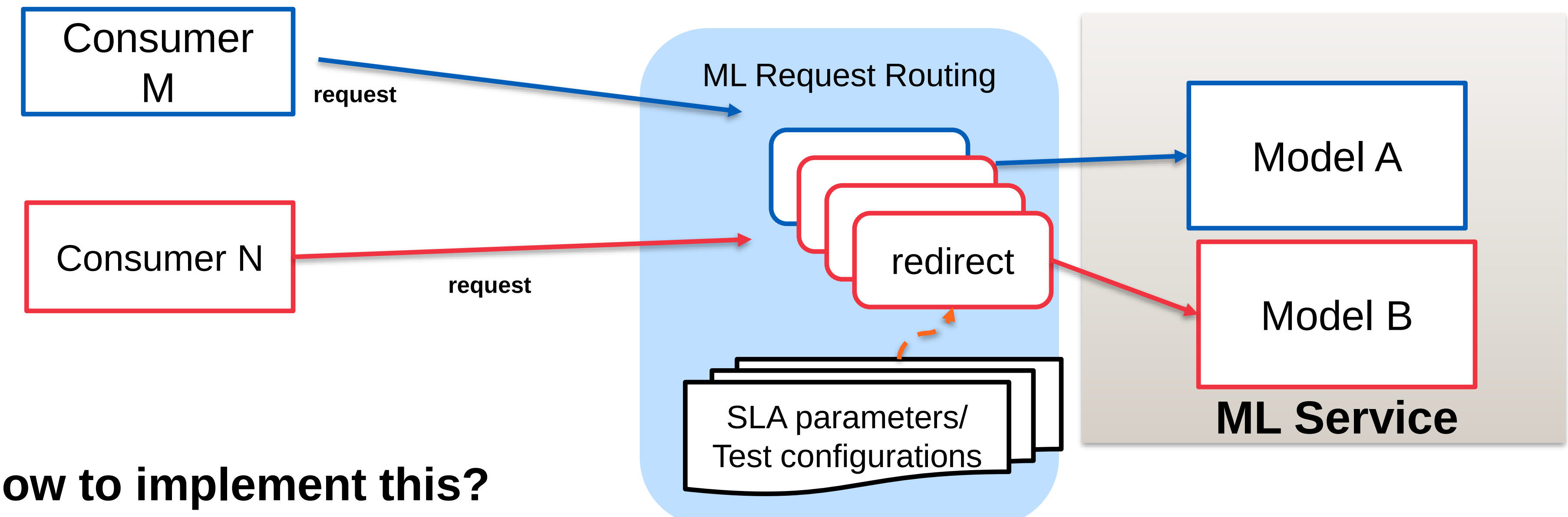


- Discussion: dealing R3E with ML workflows?
  - Elastic components?
  - Where, What, When and How

Figure source: https://predictionio.apache.org/system/

A/B testing and SLA-based serving

- **Different models with different qualities/SLAs**



How to implement this?

Example in Amazon Sagemaker

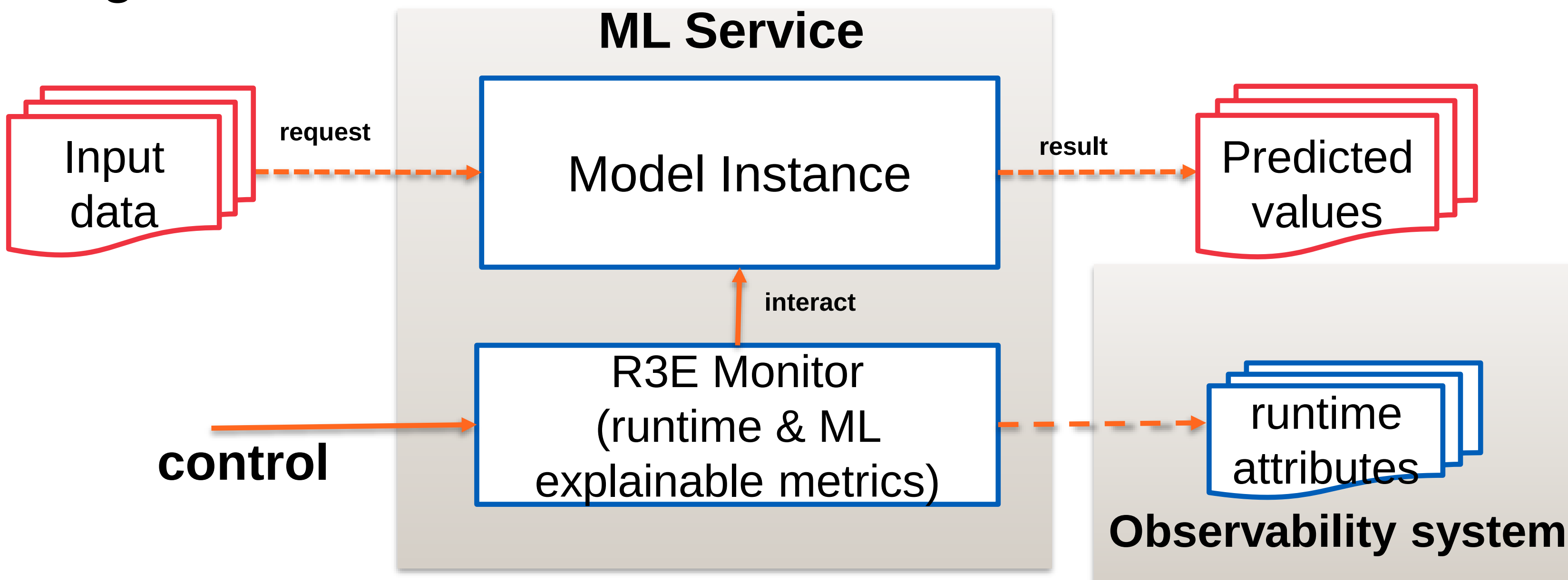
https://docs.aws.amazon.com/sagemaker/latest/dg/model-ab-testing.html

Load balancing/scaling model serving

- **ML inferencing capability in a ML model is encapsulated into a microservice or a task**
- **As a service**
  - with well-defined APIs (e.g., REST, gRPC), e.g., Dockerized service
  - using load balancing and orchestration techniques, such as Kubernetes
- **As a task**
  - using workflow management techniques to trigger new tasks
  - support scheduling, failure management and performance optimization by leveraging batch processing techniques

R3E Runtime attributes?

How to capture important metrics for observability and dynamic serving?



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What if a model is too big, need a lot of computing resources?

Study log

P1 - Take one of the following aspects:

- P1.1 - Robustness, Reliability, Resilience or Elasticity
- P1.2 – Automation management

P2 - Check one of the following aspects:

- Orchestration or ML model serving

In a *specific software framework* (F3) that you find interesting/relevant to your work:

discuss how do you see F3 supports P1 in doing P2

Thanks!

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rdsea.github.io